Heterogeneity in the Intertemporal Persistence of Health: Evidence from a Monthly Micro Panel[*]

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Abstract

Despite being widely used in health economics, dynamic models of health and healthcare typically assume that the persistence in these outcomes is the same for every individual. This paper explores individual-level heterogeneity in the persistence of health outcomes. Using simple regression methods that do not place any restriction on the distribution of the heterogeneity in persistence, the paper documents substantial heterogeneity in health, medical expenditures, and healthcare use. We show that neglecting this heterogeneity leads to estimates that overstate the average persistence and can bias the coefficients of covariates. We find that between 75% and 87% of individuals display persistence and that this persistence is related to the individuals' personality and socio-economic characteristics.

Keywords: self-reported health, healthcare utilisation, dynamic panel data, state dependence, heterogeneity.

JEL classification: I10, I12, C23

1 Introduction

Health outcome variables, like self-reported health or healthcare expenditures, exhibit a high degree of persistence: health in one period correlates strongly with health in future periods. This paper studies the individual-level heterogeneity in the state dependence of health and health-related outcomes using monthly panel data from a large representative survey of older Singaporeans, the Singapore Life Panel (SLP). Disentangling state dependence from other sources of persistence—such as permanent differences in health levels between individuals—, as well as understanding the extent and drivers of heterogeneity in state dependence, is essential for the design and evaluation of health interventions because state dependence determines the dynamics and overall long-run effects of policies that affect current health. Heterogeneity in state dependence means, for instance, that some individuals recover more slowly from health shocks than others or that some individuals benefit from certain policies for longer than others. Thus, taking into account this heterogeneity among members of the population in their responsiveness to health shocks and policies is a significant issue as it has implications for the efficiency and equitability of interventions.

We propose to model the heterogeneity in state dependence within what is perhaps the most standard framework that has been used in the health economics literature for dynamic panel data models: a linear model with a lagged dependent variable and individual fixed effects (cf., e.g., Bolhaar, Lindeboom and Van Der Klaauw, 2012). But instead of specifying a single constant coefficient on the lagged dependent variable, we specify a separate coefficient for each individual in the spirit of Pesaran and Smith (1995). The individual-specific state dependence parameters are then estimated freely without imposing any distributional assumptions, akin to the fixed effects estimation of the individual-specific constants. Because the estimator of the state-dependence coefficients, while consistent as the number of time periods increases, is biased in samples with finite time periods, we also explore the performance of bias-corrected estimators that adjust the estimates for this bias.

Dynamic models of health and healthcare are widely used in health economics, with applications ranging from self-assessed health (Carro and Traferri, 2014; Contoyannis, Jones and Rice, 2004), illness and disability (Einav, Finkelstein and Mahoney, 2018; Kapteyn, Smith and Van Soest, 2008; Hernandez-Quevedo, Jones and Rice, 2008), to health expenditures (Kools and Knoef, 2019; Rettenmaier and Wang, 2006), health care use and insurance (Buchmueller et al., 2021; Bolhaar, Lindeboom and Van Der Klaauw, 2012; Khwaja, 2010), and other health-related behaviours (Terris-Prestholt and Windmeijer, 2016). Despite differing widely in their applications and methodological approaches, all these papers find evidence for significant state dependence. Yet all of them model state dependence as driven by a single coefficient.[1] To the best of our knowledge only two papers consider heterogeneity

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[1]Some of the models are nonlinear, in which case the implied marginal effect of a shock to the lagged dependent variable would differ for individuals with different covariate values. However, this heterogeneity is highly restricted and mechanically implied by the model. See the excellent discussion on this issue in Browning and Carro (2007).

in the persistence of health, Halliday (2008) and Amengual, Bueren and Crego (2021). Both pursue approaches that are markedly different from ours and which are based on modelling the distribution of state dependence as consisting of a small number of latent groups. An advantage of our approach is that it makes no assumptions about the shape or nature of the state dependence distribution and can therefore estimate this distribution at a finely granular level. Moreover, the linear panel data model in which it is embedded makes it easy to include a large set of covariates and control for unobserved individual-specific effects, which is not straightforward in the existing approaches.[2] As the proposed approach requires estimating one state dependence parameter per individual, it is important that the longitudinal dimension of the data is sufficiently large, as we illustrate with simulations. The monthly SLP data in our estimation sample, which has four to eight times more time periods than those used in the mentioned health literature that estimates state dependence heterogeneity, satisfies this requirement comfortably. Indeed, the simulation evidence suggests that some of the yearly household survey panels widely used for health economics research, such as PSID (US Panel Study of Income Dynamics), BHPS (British Household Panel Survey) or SOEP (German Socioeconomic Panel), for which several decades of data exist, would also satisfy it, making our approach potentially broadly applicable.

There are several reasons for modelling state dependence as potentially varying between individuals. One main object of interest in the dynamic health literature cited above is disentangling state dependence from unobserved individual-specific heterogeneity (fixed effects). In practice, this often takes the form of analysing the size and statistical significance of the single coefficient on the lagged dependent variable in a fixed effects panel data model. However, if there actually is heterogeneity in state dependence, this estimator of the autoregressive coefficient is biased for the mean of the distribution, making it impossible to interpret it. Importantly, this is true even if the heterogeneity is completely random and unrelated to any of the regressors in the model or the unobserved individual-specific effects. A second object of interest in the dynamic health literature is to "control" for persistence by ways of the individual-specific effects and the lagged dependent variable in order to estimate the contemporaneous effect of some variable of interest. However, in this case, too, if heterogeneity in state dependence is present in the data generating process, misspecifying the state dependence as constant across individuals leads to bias in the estimator for the coefficient of all other regressors, in general.

Beyond making it possible to analyse the average state dependence and estimate the coefficients of covariates in the case of heterogeneous state dependence, our approach also makes it possible to study further objects of interest which go beyond those of the literature modelling state dependence as constant. In particular, in this paper, the distribution of the state dependence is in itself the key

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[2]For instance, the application in Halliday (2008) contains no controls beyond age and a quadratic function of survey year, and Amengual, Bueren and Crego (2021) does not control for individual-specific effects.

object of interest and can be analysed further, for instance by using the estimated state dependence parameters as outcome variables in regression models.

Methodologically, the approach we propose in this paper is a special case of the mean group estimator introduced in the seminal paper by Pesaran and Smith (1995), which is widely used in macro panels. Perhaps because of past computational and data constraints, the mean group estimator has not been applied to micro panels in health economics: on the one hand, the cross-sectional dimension in such panels is very large (e.g., around ten thousand in our case, while in macro applications it is often around a hundred), while, on the other hand, the longitudinal dimension has in the past been quite short (e.g., five periods in the classic dynamic panel data paper by Arellano and Bond, 1991; while in our case, we use over fifty waves of the SLP). Together, these limitations that arise in the micro panel context mean that many parameters would have to be estimated from very few observations. Here, advances in computation[3] and the monthly feature of the SLP data go a long way toward overcoming these obstacles.

However, we also implement two new techniques to account for the dynamic bias, the finite sample bias induced by the lagged dependent variable. First, we apply Empirical Bayes shrinkage (Chandra et al., 2016) to the estimated state dependence parameters; and second, we use a split panel jackknife estimator (Dhaene and Jochmans, 2015) to obtain bias-corrected estimates of the state dependence parameters as in Chudik and Pesaran (2019). Empirical Bayes shrinkage is a popular technique used in the applied microeconomic literature to deal with the imprecision of the estimates of individual-specific constants when analysing these effects is of primary interest (such as hospital or doctor fixed effects). Here, we extend this approach to the shrinkage of heterogeneous slopes. Chudik and Pesaran (2019) provide theoretical results and simulation evidence on the split panel approach to a heterogeneous dynamic panel data model such as the one in this paper. We extend the simulation evidence to study data generating processes with covariates (and therefore to be able to consider the finite sample properties of the estimators of the coefficients on covariates) and apply this method for the first time to an empirical application. Our simulation evidence suggests that with the number of time periods available in our application, the dynamic bias is not a first-order concern, with the mean group procedure delivering satisfactory estimates. However, the Empirical Bayes and the bias-correction approach improve the estimator's performance further, and they could be critical for applications with fewer time periods.

There is an active theoretical literature on heterogeneous panels. The two papers most closely related to ours are Mavroeidis, Sasaki and Welch (2015) and Okui and Yanagi (2019). The first considers a model similar to ours, but in a setting where the longitudinal dimension is short and fixed. To estimate the heterogeneity of state dependence consistently in this setting, they develop a nonpara-

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[3]For instance, sets of fixed effects in linear models can be partialled-out and estimated efficiently with moderate computing power (e.g. Correia, 2016).

metric approach. In contrast, in our setting the longitudinal dimension is long and we can rely on the substantially simpler methods of Pesaran and Smith (1995) and Chudik and Pesaran (2019). The second paper considers the case without covariates and is therefore essentially model-free. Their estimator is also equal to the mean group estimator of Pesaran and Smith (1995) on which they apply a modified Dhaene and Jochmans (2015) bias correction. Our approach is similar, but we operate in a model-based framework with covariates entering the model through a linear index.

We apply the methods to the monthly SLP survey from Singapore, which includes detailed health, health care and health expenditure questions in over 50 waves from roughly 9,000 individuals. As mentioned, this higher frequency elicitation of various health behaviours and outcomes makes it possible to assess persistence and adaptation patterns in greater detail than in previous studies. We compare standard dynamic panel data methods (such as random effects, naïve fixed effects and jackknife-corrected fixed effects, which all constrain the persistence to a single parameter) with models that allow for fully-flexible heterogeneous response parameters across individuals. Estimates of population-average persistence are obtained as simple means as well as means based on Empirical Bayes shrinkage.

We have five main findings. First, there is substantial heterogeneity across individuals in the state dependence of self-assessed health, healthcare use (as measured by at least one doctor visit) and out-of-pocket healthcare expenditures. Second, this heterogeneity drastically biases standard random-effects and fixed-effect estimators, including those that correct for the dynamic bias. The biases can be as large as 100%. Third, the heterogeneity in state dependence is only weakly correlated across the health and healthcare outcomes we considered, but in each case there is strong evidence of correlation with baseline characteristics. Fourth, personality traits have more predictive power among these baseline characteristics than economic status (income) or economic preferences (risk). Fifth, in all three outcomes, we find that about 13% to 25% of individuals display little to no state dependence, with the remaining majority of individuals having a roughly bell-shaped distribution with the majority of its mass in the positive support region.

The remainder of this paper is structured as follows. Section 2 discusses the econometric methods by introducing panel data models with heterogeneous dynamics and considering possible estimation approaches (Section 2.1), and investigating the finite sample performance of the estimators via simulation experiments (Section 2.2). Section 3 contains our analysis of the estimated heterogeneity in the persistence of health and healthcare: we give details on the Singapore Life Panel survey and the estimation sample (Section 3.1) and present the results of our estimations (Section 3.2). Section 4 concludes.

2 Econometric methods

2.1 Fixed effects estimation of panel data models with heterogenous dynamics

Consider the following stylised dynamic panel model for individual i's health or healthcare utilisation in period t:

$$y_{it} = \alpha_i + \rho y_{it-1} + x'_{it}\beta + \varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T, \tag{1}$$

where α_i are individual-specific effects, x_{it} is a vector of K covariates, and ε_{it} is an IID idiosyncratic error term that is uncorrelated with x_{it} and α_i. The α_i are treated as fixed effects in that no distributional assumption is placed on them; in particular, they may be correlated with the covariates. The use of this fixed effects auto-regressive (AR) panel model is widespread in health economics to model dynamics in health or healthcare use, which are captured by the parameter ρ. The main estimation problem with (1) discussed in the literature has been the so-called Nickell bias or dynamic bias (Nickell, 1981) that arises when the total number of time periods T is small and treated as fixed. To see the problem, consider for instance that after applying the within transformation to equation (1) to rid it of the α_i the demeaned y_{it-1} is correlated with the demeaned ε_{it}. The default approach has been to use IV and GMM approaches in which (functions of) earlier lags of the dependent variable (and covariates) are used as instruments (Anderson and Hsiao, 1981; Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998, among others). Since such procedures can suffer from the many/weak instruments problem, alternatively one can relax the view of T as fixed. Asymptotic expansions show that the dynamic bias, which is of order T, can be removed in a number of ways; for instance, by using the split-panel jackknife (SPJ) estimator (Dhaene and Jochmans, 2015; Chudik, Pesaran and Yang, 2018).

Dynamic panel data models such as (1) have been used to separate different sources of persistence in health, such as "individual heterogeneity" (as captured by the individual effects α_i) and state dependence (as captured by the lagged dependent variable). The main object of interest of this paper is to examine the individual heterogeneity *in* state dependence, that is, the distribution of state dependence over individuals. To that end, we consider a heterogeneous version of (1), which we will refer to as the heterogeneous auto-regressive (HAR) panel model, in which state dependence is individual-specific, too:

$$y_{it} = \alpha_i + \rho_i y_{it-1} + x'_{it}\beta + \varepsilon_{it}, \tag{2}$$

where in contrast to (1) this model explicitly specifies individual heterogeneity in the coefficient of the lagged dependent variable (ρ_i). The default in the dynamic health literature is to assume that

$\rho = \rho_i$ for all individuals, ignoring this type of heterogeneity. While in this paper the goal is to study the heterogeneity in itself and its correlates with observables, sometimes the interest lies only in the *average* state dependence, $\bar{\rho}_i = N^{-1} \sum_N \rho_i$. In that case, often the estimates $\hat{\rho}$ from homogenous AR models such as (1) are treated as estimates of the *average* state dependence, $\bar{\rho}_i = N^{-1} \sum_N \rho_i$. However, it is known that $\hat{\rho}$ from model (1) is not consistent for $\bar{\rho}$ (Pesaran and Smith, 1995), and, as we illustrate in simulations below, even in very simple data generating processes the estimates of models that ignore heterogeneity in state dependence can be severely biased. Thus, if one wrongly assumes $\rho_i = \rho$ and estimates model (1), there are now two sources of bias: the Nickell bias and the heterogeneity bias.

We propose to implement and compare two solutions to this problem. First, since the dynamic bias dissipates as T increases, but not the heterogeneity bias, a simple approach is to neglect the dynamic bias and focus only on the heterogeneity bias by estimating each separate ρ_i and then averaging over all N estimates. This is the Group Mean estimator of Pesaran and Smith (1995). In the context of the SLP data, this approach relies on the substantial longitudinal dimension of about 50 periods, which could imply that the residual dynamic bias might be negligible. In a variant of this approach, we explore potential improvements in the estimation quality of $\bar{\rho}$ that could be gained from refining the procedure of averaging over the $\hat{\rho}_i$: Instead of the simple average as in the Group Mean estimator, we also obtain an estimate of $\bar{\rho}$ by applying Empirical Bayes shrinkage to the $\hat{\rho}_i$ when averaging them. Finally, the second solution approach is also based on the Group Mean estimator, but instead of applying the averaging over ρ_i to estimates of a naïve fixed effects estimator, we obtain the estimates for ρ_i from a bias-corrected estimator that addresses the dynamic bias: the split-panel jackknife estimator for heterogeneous panel models proposed by Chudik and Pesaran (2019).

Heterogeneous panel models such as (2) are common in empirical macroeconomics (Breitung, 2015). While they have been developed for and applied in macroeconomic settings, much less is known about the performance of these models in micro panels. An essential feature which makes these models attractive for health economics is that in order to get purely data-driven and consistent estimates of ρ_i (as well as α_i) none of the heterogeneity is constrained by distributional assumptions. That is, these terms are treated as fixed effects to be estimated. However, different from the default macroeconomic setup, where i often indexes countries, in the context of the Singapore Life Panel the individual dimension N is (very) large. Another difference is that in the macroeconomic approach the interest sometimes lies in long-term changes in the outcome (such as $\rho_i/(1 - \rho_i)$ and $\beta/(1 - \rho_i)$) rather than the short-term dynamics (ρ_i and β). These long-term objects of interest are often estimated directly by transforming the model into what is called its error-correction form and using maximum likelihood estimation to estimate the resulting nonlinear model. In contrast, we estimate model (2) for the Singapore Life Panel directly without transformation using what is arguably the simplest possible approach: OLS with sets of indicator or dummy variables to capture individual (and time) effects,

and interactions between a set of individual dummies and the lagged dependent variable to estimate ρ_i. Recent computational advances (Correia, 2016) make it possible to estimate the large number of parameters of model (2), which is in the order of $2N + T + K$, rapidly and efficiently.

While the default in the macroeconomic literature has been to ignore the dynamic bias, the results for the dynamic bias in the AR panel model (1) directly extend to the HAR model. As in the AR model, the dynamic bias in the autoregressive coefficients (ρ_i) spills over to the covariate coefficients in the HAR model (2). And as in the AR model, the dynamic bias increases when fewer covariates with $\beta \neq 0$ are included in the HAR model. In contrast, in the health literature, the default has been to ignore the heterogeneity bias. As mentioned, if an AR model is assumed when the DGP is a HAR model, the estimated $\hat{\rho}$ is inconsistent for $E(\rho_i)$. In general, the asymptotic bias in $\hat{\rho}$ spills over to the covariates, biasing $\hat{\beta}$. This will generally happen even when the ρ_i are statistically independent of α_i and x_{it}. Thus, the presence of heterogeneity in state dependence has important implications for the conventional strategy in health economics of studying heterogeneity via interactions (for instance, by estimating an augmented version of model (1) with the additional interaction variable $y_{it-1}d_i$, where d_i is an indicator of some group membership such as gender). Unless the group indicator in the interaction (d_i) fully captures the heterogeneity, the coefficient estimates on the auto-regressive terms and covariates will still be inconsistent. The approach suggested in this paper, by contrast, provides a straightforward way of obtaining consistent estimates of group differences in average state dependence: first, estimate all ρ_i; then, regress the estimated ρ_i on any regressors of interest such as d_i.

2.2 Numerical experiments

Data Generating Process

To investigate the finite sample performance of the various estimators for the HAR model (2) that we have discussed above we design a series of Monte Carlo simulation experiments for settings similar to our monthly micro data. We use a simple data generating process (DGP) corresponding to (2) with a single regressor x_{it}. Similar to the Singapore Life Panel data used, the number of periods is set to $T = 50$. We only use $N = 500$, since the quality of individual-specific parameters such as ρ_i is determined by T. The model is

$$y_{i0} \sim Normal(0, 0.25) \tag{3}$$

$$y_{it} = \alpha_i + \rho_i y_{it-1} + 0.5x_{it} + \varepsilon_{it}, \quad \text{if } t \geq 1, \tag{4}$$

for $i = 1\dots, 500$ and $t = 1, \dots, 50$. The error is drawn from $\varepsilon \sim Normal(0, 0.5)$ and $x_{it} = \bar{x}_i + \nu + 0.001t^2$, where $\nu \sim Normal(0, 0.25)$. The variables $(\alpha_i, \rho_i, \bar{x}_i)$ follow a trivariate normal distribution

with means $(1, 0.5, 1)'$, and α_i and $\bar{x}_i$ have standard deviations $\sigma_\alpha = 0.25$ and $\sigma_{\bar{x}} = 1$. The parameters that we vary in the simulation experiments are the heterogeneity in the auto-regressive parameter ρ_i. We consider different standard deviations, $\sigma_\rho = \{0, 0.125, 0.25\}$ as well as a case in which the variance of ρ_i is heteroskedastic with $E(\sigma_{\rho,i}) = 0.15$. In this case, we draw ρ_i from five latent groups with standard deviations $0.05, 0.10, \ldots, 0.25$. Each latent group has the same probability mass. The second set of parameters that we vary is the correlation between α_i, ρ_i, and $\bar{x}_i$,

$$
C_{\alpha\rho\bar{x}} = \begin{pmatrix} 1, & \tau_{\alpha\rho}, & \tau_{\alpha\bar{x}} \\ \tau_{\alpha\rho}, & 1, & \tau_{\bar{x}\rho} \\ \tau_{\alpha\bar{x}}, & \tau_{\bar{x}\rho}, & 1 \end{pmatrix}, \tag{5}
$$

where, for instance, $\tau_{\alpha\rho} = \sigma_{\alpha\rho}/(\sigma_\alpha\sigma_\rho)$ and $\sigma_{\alpha\rho}$ is the covariance between α_i and ρ_i, and the other parameters in (5) are defined analogously. We consider a baseline DGP with $C_{\alpha\rho\bar{x}} = C^B$ where α_i, ρ_i, and $\bar{x}_i$ are uncorrelated and an alternative DGP with $C_{\alpha\rho\bar{x}} = C^A$ with non-zero correlations:

$$
C^B = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \qquad C^A = \begin{pmatrix} 1 & -0.3 & -0.8 \\ -0.3 & 1 & 0.5 \\ -0.8 & 0.5 & 1 \end{pmatrix}. \tag{6}
$$

Further correlation structures are considered in robustness checks and discussed below.

ESTIMATORS

We compare six possible estimators in the Monte Carlo simulation focussing on the question of how well they perform in obtaining an estimate of $E(\rho_i)$, the mean of the autoregressive coefficient. The first three ignore the individual heterogeneity in ρ_i; that is, they assume $\rho_i = \rho$ for all i as in equation (1), and we use $\hat{\rho}$ as their estimate of the mean, $E(\rho_i)$. The latter three obtain an estimate of each ρ_i, which is then combined into an average $\bar{\rho}$. The estimators in the first category are the random effects estimator (RE), the fixed effects estimator (FE) and a bias-corrected fixed effects estimator (BC-FE). This last estimator is a split-sample jackknife estimator that nonparametrically removes the Nickell bias and other finite sample bias due to T being finite (Dhaene and Jochmans, 2015). In essence, the BC-FE estimation procedure consists in splitting the estimation sample into two halves at the middle period $T/2$ and estimating FE in each half, as well as in the full sample. By comparing the average estimate in the half-sized samples to the estimate in the full sample, it is possible to infer the magnitude of the order-T bias (which is larger in the small samples and decreases with T) and subtract the bias from the full sample estimate.

The first estimator that takes into account the individual heterogeneity in ρ_i is the FE estimator with, in addition to a set of individual dummy variables, a set of interactions between the individual dummies and the lagged dependent variables. The estimate of $E(\rho_i)$ is the simple sample average of

the estimated $\hat{\rho}_i$, which is why this estimator is called the simple group mean estimator ("Simple" in table headers). The second estimator differs from the first only in how the individual $\hat{\rho}_i$ are averaged. Instead of the simple average, we use the so-called empirical Bayes approach ("EBayes"), in which, loosely speaking, the $\hat{\rho}_i$ are weighted by the inverse of their estimated variance. While these two estimators take into account the heterogeneity in ρ_i, they do not correct estimates for possible Nickell and small-T bias. Thus, the last estimator takes the split-panel jackknife approach to the model with heterogeneous autoregressive coefficients ("iSPJ").

RESULTS FOR $E(\rho_i)$

The results of the Monte Carlo experiment are presented in Tables 1, for the baseline DGP where the ρ_i are completely random and uncorrelated to both α_i and the observable covariate, and Table 2, for the alternative DGP where the ρ_i are correlated with the individual fixed effects α_i and the covariate x_{it}. In the top half, the tables' columns report estimates of $E(\rho_i)$ for each of the six different estimators across four rows representing four different DGPs that vary in terms of the heterogeneity in ρ_i as captured by its standard deviation, σ_ρ. In the top row, there is no heterogeneity ("*Panel A*: $\sigma_\rho = 0$") and the model simplifies to the standard constant-effects dynamic panel data model from equation (1) as assumed by the estimators in columns (1)-(3). The lower half of the tables presents the corresponding estimates for β. For both parameters β and $E(\rho)$, the true value is 0.5.

A look at the top row ("*Panel A*: $\sigma_\rho = 0$") of Table 1, shows that the random effects estimator is biased even in this simple DGP ($\hat{\rho} = 0.66$). If ρ were equal to zero, RE would be the most efficient estimator under this DGP. But when $\rho \neq 0$ the lagged dependent variable, which contains α_i, is mechanically correlated with the estimation error, which also contains α_i in the RE approach. All other estimators condition on α_i and so do not have this problem. Their estimates are all close to the true value of 0.5, although the FE estimator and the mean group estimator (and therefore the EBayes estimator, too) suffer from slight attenuation bias due to some remaining Nickell bias. The estimators that correct for this via the split panel jackknife (BC-FE and iSPJ) are virtually unbiased.

However, the introduction of even a modest level of heterogeneity in ρ_i (*Panel B*) has quite dramatic effects on the estimates of the constant-effects model estimators of columns (1)-(3), with biases ranging from over 60 to close to 100 percent (i.e., 0.812/0.5 and 0.969/0.5). Biases for these estimators worsen further for increased levels of heterogeneity (*Panel C*) or a similar level of average heterogeneity but with heteroskedasticity (*Panel D*). These results are quite remarkable, since estimates of ρ close to 1 or even greater than 1 (as in *Panel C*) could lead a researcher not aware of potential heterogeneity in ρ to erroneously believe that the model is not stationary ($\rho > 1$), when in reality every single ρ_i is in fact smaller than 1. In contrast, in each of these cases, the simple group mean estimator (column 4) delivers a good performance with a downward bias that is less than 10 percent. The more sophisticated group mean estimators EBayes and iSPJ obtain estimates that are even less biased.

RESULTS FOR β

The lower half of Table 1 contains the corresponding results for the estimates of the coefficient on the covariate, β. The results mirror those for $E(\rho)$. The performance of all estimators except for RE is good in the case of no heterogeneity in ρ (*Panel E*). But with heterogeneity in ρ_i all the estimators that assume no heterogeneity produce strongly distorted estimates of β, even though ρ_i in uncorrelated with both α_i and x_{it}. Similar to the case of the estimates of $E(\rho_i)$ before, the biases can easily be so large as to lead to seriously misleading inference. For instance, in *Panel G*, the average RE estimate of β is essentially zero (-0.005), when the true value is 0.5. Researchers relying on BC-FE estimates might even conclude that the effect of x_{it} is negative (-0.087). In contrast, the estimators that account for the heterogeneity in ρ_i produce estimates of β that are close to the true value.[4]

ROBUSTNESS CHECKS

To obtain the results in Table 2, the ρ_i were drawn as being correlated with α_i and x_{it} according to the correlation matrix C^A in (6). The table shows that the presence of such correlation does not change any of the results substantially. The estimates are quite similar. We investigated further correlation structures (results not reported) where we changed both the sign and strength of the correlation. In all cases, the results were very similar to the ones reported in Tables 1 and 2. We also considered a DGP with the special case of the (demeaned) x_{it} being independent over time, $x_{it} = \bar{x}_i + \nu$, instead of serially correlated as in our baseline. In this case, the biases are limited to $E(\rho_i)$ (and similar to the ones reported in the tables) but do not spill over to β. Unfortunately, in many real-world applications x_{it} are serially correlated, so heterogeneity in ρ_i might be an issue for researchers even if their interest is limited to β. Finally, we also repeated the simulations for a different, lower value of $E(\rho_i) = 0.2$, which is close to our results in the application. Again, results were qualitatively similar.

SIMULATIONS INVESTIGATING THE ROLE OF T

We conclude the simulations by exploring the role of T in obtaining reliable estimates of the average state dependence parameter, $E(\rho_i)$. Results are collected in Figure 1. We present estimates for the FE, simple group mean estimator and iSPJ for, successively, T=6, 10, 25, 50. The smallest possible time period is $T = 6$ as iSPJ halves the sample along the time dimension, resulting in samples of three periods, and one further period is lost due to the lagged dependent variable. The right-hand-side panel of Figure 1 introduces an additional empirical feature: missing observations. In the estimates of that panel, 20 per cent of the observations were deleted at random. In our DGP, small-T bias (which always leads to attenuation bias) and heterogeneity bias (which here leads to overestimation) work in opposing directions. Thus, with a low number of time periods, these biases almost cancel out for FE. However, already at T=10, the heterogeneity bias dominates, and FE is severely distorted. In

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[4]There are no results for EBayes since there is no heterogeneity in β and therefore the EBayes estimate for β is the same as the one in column (4).

contrast, the iSPJ approach delivers very good results from as little as 10 time periods. The simple mean group estimator without bias-correction requires a larger longitudinal dimension for the dynamic bias to dissipate naturally. As seen before, at T=50, the remaining bias is small.

CONCLUSION

To summarise, our simulations have illustrated that with the number of periods at hand, neglecting heterogeneity in ρ_i leads to substantial biases, whereas the main concern typically raised in dynamic fixed-T panel data, Nickell bias, play a more limited role. While the more sophisticated approaches can serve to further address these, especially when T is smaller, the gains from using these methods over more simple and robust approaches such as the mean group estimator are more modest when T is around 50, as in our empirical application.

3   Estimates of the heterogeneity in the persistence of health and healthcare

3.1   The Singapore Life Panel: Data and institutional setting

Data for this analysis is drawn from the Singapore Life Panel (SLP), a panel survey which has been collecting data from a population-representative internet survey of older Singaporeans, operating every month since 2015.

Initial recruitment to the SLP took place from May to July 2015 and utilized a random sample of 4% of all households that contained at least one Singaporean citizen or permanent resident aged 50 to 69 years of age. Traditional methods were used to invite these individuals and their spouses to participate in the panel, including introductory letters followed-up by door-knocking and phone calls. Of the 22,500 addresses contacted, individuals from 11,500 households elected to join the panel, implying a 52% response rate. Including spouses, 16,000 respondents joined the panel.

This base sample are highly representative of the corresponding national population for this age group on demographic and socioeconomic characteristics including gender, marital status, ethnicity, labour force participation, income and expenditure (Vaithianathan et al., 2018). However, there has been a mild attrition effect in each month since then, mostly driven by respondents with more education being more likely to complete subsequent surveys.

Every month since September 2015, respondents have been invited to log into the online platform and participate in a 15 minute survey in exchange for SGD$10 of supermarket vouchers. In a typical month, 7,700 respondents will complete the survey: 69% of their own accord, 25% with help from a family

member, 5% with the help over the phone from a Singapore Management University student, and 1% at an in-person appointment. We use data through to December 2019, and restrict the sample to those individuals who have answered at least 10 waves of data and who provided non-missing responses to the key variables below. This combines to roughly 350,000 observations, from 8,500 individuals over 53 months. Due to lower attrition among respondents with high education, this restricted sample is slightlly over-representative of both the highly-educated and Chinese populations. For example, 35% of our sample have a post-secondary qualification, compared to 30% among the equivalent age cohort in the Singapore population. Similarly, 86% in our sample are Chinese, compared to 79% of the wider population Department of Statistics (2010). Age and gender remain highly population-representative.

Questions repeated every month include employment status, sources of income, expenditure across 44 categories, health status and subjective well-being. We make use of three health outcome variables in this paper:

1. Self-assessed bad health. We construct this variable as an average across two related measures: *Self-assessed health*, measured by asking "*Would you say your health is excellent, very good, good, fair, or poor?*," and *health satisfaction* assessed on a five-point Likert scale from "*very dissatisfied*" to "*very satisfied.*" We rescale the resulting variable, which has 10 points of support, to the unit interval ($y_{it} = 0, 0.1, 0.2, \ldots, 1$); where 0 indicates the best and 1 the worst health.[5]

2. Medical expenditures. Measured in Singapore dollars, we use this variable to capture behavioural responses in healthcare utilisation. Medical expenditures are the sum of monthly spending on medications, outpatient services, hospital services and home nursing. It includes both out-of-pocket expenditure and any expenses paid from MediSave, the mandatory individual health savings account.

3. Doctor visits. A binary indicator variable of whether the individual visited a doctor in the past month, mostly free of charge.

Figure 2 presents the overall distributions of each of these three variables and the distributions of their individual averages, visualising the variation in our health outcome measures.

The healthcare use and expenditures take place within a healthcare system which is primarily government-run, but funded via individual mandatory health savings accounts and private health insurance, supplemented by private healthcare providers and targeted support. All citizens and permanent residents must contribute 8% to 10.5% of their wages to a national savings account called MediSave, which is administered by the Central Provident Fund (CPF), a government entity (Central Provident Fund Board, 2020). Funds from this account must be used to purchase MediShield Life, a basic health insurance plan which covers large medical bills from public hospitals (Ministry of Health, 2020). Individuals can also use their MediSave funds to purchase approved supplementary private health insurance, and to cover approved health expenditures up to posted withdrawal limits. For those Singaporeans who

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[5]We code having higher values of the variable as indicating worse health in order to align it with the other two outcomes (medical expenditures and doctor visits) where higher values also indicate higher health-related needs.

cannot otherwise afford healthcare, assistance is provided via Medifund and targeted subsidies.

3.2   Estimation results

To estimate the heterogeneity in the persistence of each of the three outcome variables (self-assessed bad health, medical expenditures and doctor visits) we estimate for each of them model (1) and (2) by RE, FE, BC-FE, the simple mean group (MG) estimator and the bias-corrected heterogeneous split panel jackknife (iSPJ) estimator. Besides individual-specific constants and the lagged dependent variable, the specification includes year fixed effects, month-of-the-year fixed effects, and a quadratic function of age. Standard errors are clustered at the household level.

ESTIMATES OF THE AVERAGE PERSISTENCE

Table 3 presents the estimates in a format that is similar to the one used for the simulation results, focussing on the estimation of $E(\rho_i)$, the average state dependence in health, expenses and doctor visits. The pattern of the results in Table 3 is also in line with the simulations in each of the panels A to C corresponding to the three outcomes. First, the random effects estimator of the homogenous ρ model (1) (column 1) yields results that are strikingly different from the other estimators, which all condition on individual-specific constants α_i and therefore are robust against correlation between α_i and the regressors. The RE estimates of state dependence are about twice as large as those of the the two remaining estimators of the homogenous ρ model, FE and BC-FE in columns (2) and (3), and range from 0.859 for self-assessed bad health to 0.299 for medical expenditures. Second, FE and BC-FE produce estimates of the average state dependence that are noticeably larger than those from the estimators that account for heterogeneity in ρ_i, shown in columns (4)-(6). Because the dynamic bias correction increases the estimate, this overestimation of the (average) state dependence is more pronounced for BC-FE than for FE.

Third, the estimators of the heterogeneous persistence model produce results that are consistent with each other. For *self-assessed bad health*, the simple and empirical-bayes-shrunken MG estimate are both 0.237, while the split-panel jackknife bias-corrected estimate of the average persistence is 0.268. These estimates are thus only about half as large as the BC-FE estimate. While the iSPJ estimator has favourable theoretical properties, a practical disadvantage is that data on individuals with gaps in their responses have to be dropped from the estimation (that is, individuals who skipped their interview in one or more months). This is why the number of observations is lower for iSPJ. This is also the likely reason why there is a slightly larger discrepancy between the MG estimates and the iSPJ estimate for *medical expenses* in *Panel B*, where the Simple and EBayes MG estimates are 0.111 and 0.131 while iSPJ is 0.040, although with a standard error that makes it not statistically different to the MG estimates. Again, the BC-FE estimate is about twice that of the MG estimates.

For *doctor visits* in *Panel C*, the three heterogenous ρ_i estimates are again very close to each other at 0.150, 0.150 and 0.154, while BC-FE is about 50 percent larger. Fourth, the table reports the share of the estimated ρ_i that are statistically significant. Despite the estimated average persistence being of a moderate level, most $\hat{\rho}_i$ are statistically significant. This ranges from 74.3 percent for medical expenditure to 94.3 and 96.4 percent for self-assessed bad health and doctor visits, respectively.

In conclusion, estimating the heterogenous ρ_i model, we find strong evidence of state dependence in each of the outcomes. However, neglecting this heterogeneity and estimating a constant-ρ model would substantially overestimate the average state dependence in these health outcomes. Since we found that the simple, uncorrected estimates of the heterogenous model are largely similar to the bias-corrected ones and that they have the advantage of handling gaps in the observations more easily, we use these estimates as the basis for investigating the distribution of the estimated persistence further.

THE DISTRIBUTION OF THE ESTIMATED PERSISTENCE

Figure 3 presents histograms of the estimated $\hat{\rho}_i$ for each of the three health outcomes. Despite having been estimated freely and without any constraint, the shapes of the three histograms display broad similarities. While the outcomes capture very different aspects of healthcare, such as subjective health, healthcare cost, and healthcare use, all three histograms are bell-shaped and have a spike in density around the value of 0. The vast majority of the density mass is positive or zero, with only a small fraction being negative, mainly on the interval (-0.5,0). While expenditures and visits have also little mass beyond 0.5, the figure shows that self-assessed bad health has a larger mass with such high persistence. This basic pattern is robust to the number of lags of the dependent variable included in the model.

We performed two robustness checks on the estimation of the distribution of the heterogeneity in the persistence of these health outcomes. First, the heterogeneous auto-regressive model (2) with one single lag of the dependent variable is a stylised representation of the dynamics in these health outcomes. To make sure that by limiting the model to one lag we are not missing crucial higher-order dynamics, we re-estimated the models for each of the three outcomes including additional lags of the dependent variable. The resulting distributions of persistence are similar (cf. Figure A1 in the appendix), reassuring us that the simple HAR model with one lag captures the essential differences in dynamics across individuals. Second, since the quality of the estimates of ρ_i depends on the number of periods available per individual, a concern is that lower-quality estimates of ρ_i from individuals observed for fewer periods distort the shape of the estimated histogram. To address this, we plotted the histograms keeping only the $\hat{\rho}_i$ of individuals observed for 30 or more periods in the data. The resulting distributions of persistence (cf. Figure A2) are also virtually identical to the ones in Figure 3.

To investigate whether individual-level persistence is correlated across the outcome domains, we compute pairwise correlation coefficients, such as $Corr(\hat{\rho}_i^{SAH}, \hat{\rho}_i^{Oop})$, the correlation between the estimated persistence in self-assessed bad health and the estimated persistence in medical expenditures. Moreover, similarly, we can also determine how individual persistence ρ_i correlates with the individual constants or "fixed effects" α_i. The latter represent permanent or underlying levels of the health-related outcomes (net of covariates), while the former give an indication of how fast or slow an individual returns to these underlying levels after a shock. Table 4 presents the full correlation matrix between these two heterogeneity terms.

Considering the lower part of Table 4 which contains the correlations between the ρ_i, the results indicate that there is a weak positive correlation between persistence in self-assessed bad health and persistence in doctor visits (0.118) as well as between persistence in doctor visits and persistence in medical expenditures (0.089). The persistence in health and expenditures are essentially uncorrelated (0.016). These contrasts with the correlation among individual averages or long-term individual levels, α_i, where we find consistently strong positive correlations. The correlation between the long-term health level and the corresponding long-term expenditure and doctor visit levels are 0.517 and 0.543. The correlation in α_i^{Exp} and α_i^{Doc} is 0.968. Of the cross-correlations between persistence and permanent levels, most are close to zero, with two exceptions. First, there is a strong negative correlation between persistence and levels in self-assessed bad health (-0.597). Sadly, this implies that a good shock in self-assessed health for those in long-term bad health tend to be short-lived, while bad shocks for those in long-term good health tend to be persistent. Second, there is a slight negative correlation between persistence in doctor visits and long-term levels of self-assessed bad health (-0.073): those in good long-term health tend to display a somewhat stronger persistence in doctor visits.

THE SOCIAL GRADIENT IN PERSISTENCE

Is the heterogeneity in persistence random? If not, can it be predicted by observables? Which traits are associated with high persistence? To answer these questions we use regression models where the estimated $\hat{\rho}_i$ are the dependent variables. As potential determinants of the persistence we consider socio-economic variables such as gender (an indicator variable for female), marital status (an indicator for being married), a quadratic function in age, years of schooling and (the natural logarithm of) household income. We also consider risk attitudes as a measure of economic preferences, and variables for the "big five" personality traits.

To take into account the distributions of the estimated persistence parameters (Figure 3), which are bell-shaped but with a prominent spike around zero, we use finite mixture modelling. We assume that the observed distribution is a mix of two latent (or unobserved) normally-distributed groups or classes. One class produces the overall bell shape with positive mean and most mass in the positive domain. The other class produces the spike around zero as a normal distribution centred at zero and

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with a small variance. This modelling is consistent with the idea of the distribution of ρ_i having a discrete mass point at zero. Since we observe estimates of the persistence ($\hat{\rho}_i$) rather than the true ρ_i, the estimation error in $\hat{\rho}_i$ naturally transforms the true mass point at zero of ρ_i into a distribution around zero for $\hat{\rho}_i$. Finally, each of the two classes has a different conditional mean function specified as a linear index in the covariates mentioned above. Formally, let the probability density function of $\hat{\rho}_i$ be

$$f(\hat{\rho}_i|x_i) = \pi\, f_1(\hat{\rho}_i|x_i) + (1 - \pi)\, f_2(\hat{\rho}_i|x_i), \tag{7}$$

where

$$f_1(\hat{\rho}_i|x_i) \sim N(x_i'\gamma_1, \sigma_1) \quad \text{and} \quad f_2(\hat{\rho}_i|x_i) \sim N(x_i'\gamma_2, \sigma_2), \tag{8}$$

and $\pi \in (0,1)$ denotes the proportion of class 1 in the population. We estimate the parameters of model (7)-(8) by maximum likelihood based on the sample log likelihood $\mathcal{L}_n(\pi, \gamma_1, \gamma_2, \sigma_1, \sigma_2) = \sum_{i=1}^n \ln f(\hat{\rho}_i|x_i)$.

We consider three specifications for the two mean functions, $E(\hat{\rho}_i|x_i) = x_i\gamma_1$ (for those i in class 1) and $E(\hat{\rho}_i|x_i) = x_i\gamma_2$ (for those in class 2). In the first specification, we exclude all variables x_i and the conditional means are just constants ($\gamma_{1,0}$ and $\gamma_{2,0}$); in the second, we include socio-economic variables in x_i but exclude the economic preference and personality variables; and in the third, we include both socio-economic variables as well as economic preferences and personality. The results for these three specifications, for each of the three health outcomes, are given in Tables 5-7. In the tables, classes are always ordered such that the class with the higher conditional mean is defined as 'class 2'.

From the goodness-of-fit criteria reported in the tables—the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC)—it is immediately clear that the full specification with both sets of covariates, socioeconomic and preferences/personality, is the preferred one as it produces the smallest values of the criteria and thus the best fit (while penalising models for larger numbers of parameters). Using likelihood ratio tests, we can also formally test for joint significance of these sets of variables. For instance, both the set of socioeconomic characteristics (gender, marital status, age, education and income) as well as the set of preferences/personality are each highly jointly statistically significant ($p < 0.001$) for predicting the persistence in self-assessed health (columns 1 and 2) and in medical expenditures (columns 3 and 4). For doctor visits (columns 5 and 6), we find no statistically significant effect of socioeconomic characteristics, but again the set of preferences/personality is highly significant.

Figure 4 presents a further visual confirmation of the goodness-of-fit of the finite mixture model for self-assessed bad health from Table 7. Each ρ_i has been predicted as either class 1 (if $\hat{\pi}_i > 0.5$) or class 2 (if $\hat{\pi}_i \leq 0.5$) and the resulting histograms of the two predicted classes are presented on the left-hand-side graph. From the graph it is clear that the class assignment coincides with the intuitive

and assumed division of classes into the spike at zero (class 1) and the bell-shape over mostly the positive domain of ρ_i (class 2). The right-hand-side graph plots the point-wise marginal predicted density (that is, $\hat{f}(\hat{\rho}_i|x)$ from equation 7), which indicates that the estimated model also replicates well the shape of the raw empirical distribution of the data. The corresponding figures for the other two outcomes look similar and can be found in the appendix (cf. Figure A3).

Thus, overall, the findings show that the heterogeneity in the persistence in health, expenditures, and doctor visits is not random. Socioeconomic variables as well as personality traits are statistically significant predictors of this heterogeneity and improve the fit of the estimation; in the case of personality variables, substantially so. At the level of individual predictors the picture is less precise, with several variables not being individually statistically significant. Of course, for class 1, we expect the variables to have coefficients equal to zero since we hypothesise $E(\hat{\rho}_i) = 0$, consistent with the spike at zero. Indeed, the coefficients in columns (1), (3) and (5) of Table 7 are almost all insignificant, and the class means are close to zero (-0.027, -0.024 and -0.054).

For the coefficients of the mean function of class 2 (i.e. for individuals with non-zero persistence), the most precise results are obtained for health expenditures (column 4), where higher age, education and income are all associated with a higher average persistence. This might be an indication that when individuals with a higher socio-economic status are hit with a health shock, they use more or longer follow-up treatments and tests associated with out-of-pocket costs. Apart from this case, however, economic variables such as household income and risk attitudes are not found to be individually significant in the preferred models (Table 7). This contrasts with the personality traits, where individually significant variables are found in every outcome (columns 2, 4 and 6).

4   Conclusions

Methodologically, the focus of much of the research using dynamic health economics models has been on addressing Nickell bias. As both longer and higher-frequency micro panel datasets are increasingly becoming available to health economists, we argue that there should be a shift in the attention of researchers towards also addressing heterogeneity bias, an issue which so far has been largely neglected in the dynamic health literature. As we demonstrated with a monthly panel survey from Singapore, there is extensive evidence of heterogeneity in state dependence in common and widely-used outcome variables in this literature, such as subjective health, medical expenditures and doctor visits. In our empirical application, for instance, we found that neglecting heterogeneity led to overestimating the average state dependence between 50% to 100%.

Heterogeneity in state dependence is different from heterogeneity in the effect of control variables in that if neglected it generally leads to biases in both the estimate of the average state dependence as well

as the coefficients of control variables even if the heterogeneity is fully independent of the covariates or the individual-specific effects. A consequence of this is that heterogeneity in state dependence should not be investigated in the usual way by creating interactions between the dependent variable and variables of interest. Instead, we propose to freely estimate the heterogeneity first (that is, without imposing any distributional assumptions on the heterogeneity), and then, in a second step, analyse how the heterogeneity relates to observables of interest. Using this approach with the Singaporean data, we found that the persistence in health outcomes was correlated with socioeconomic characteristics, personality traits and economic preferences.

The proposed estimation methods are easy to implement and are now computationally feasible even in large datasets. They are based on methods that are well-established in econometrics and macroeconomics (Pesaran and Smith, 1995), and which have been further refined recently (Chudik and Pesaran, 2019). This paper applied these methods for the first time to dynamic health models. Our simulations showed that with the data at hand the basic group mean estimator performs well and is effective at estimating heterogeneity. For shorter data, the bias-corrected and empirical-bayes-shrinkage versions can substantially improve the performance. While in macroeconomics the focus has been mainly on the average state dependence and, in particular, the average long-run effect, in our context we have focussed on further analysing the heterogeneity. We found that between 13% and 25% of individuals had no state dependence in the health outcomes we considered, while the remainder's distribution of state dependence was mainly positive and bell-shaped. The results showed state dependence to be only weakly correlated across health outcomes and revealed different patterns of correlation between the heterogeneity in state dependence and the heterogeneity in long-term levels depending on the outcome. Such associations of persistence with socio-economic and other characteristics, as well as its correlation with long-term levels, are important from a policy perspective since they have implications for the efficiency and equitability of interventions targeting these health outcomes by amplifying or reducing differences between population subgroups.

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Tables and figures

Table 1: MONTE CARLO SIMULATION RESULTS: ZERO CORRELATION

I. Average estimate of $E(\rho_i)$. (True value in DGP: $E(\rho_i) = 0.500$)

	Estimators for AR models			Estimators for HAR models		
	RE	FE	BC-FE	MG	EB-MG	BC-MG
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: $\sigma_\rho = 0$						
y_{it-1}	0.663	0.477	0.503	0.457	0.471	0.500
(sd)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Panel B: $\sigma_\rho = 0.125$						
y_{it-1}	0.964	0.812	0.969	0.456	0.472	0.498
(sd)	(0.008)	(0.022)	(0.030)	(0.002)	(0.003)	(0.003)
Panel C: $\sigma_\rho = 0.250$						
y_{it-1}	1.027	0.983	1.038	0.454	0.469	0.492
(sd)	(0.001)	(0.002)	(0.004)	(0.002)	(0.002)	(0.003)
Panel D: $E(\sigma_{\rho,i}) = 0.150$						
y_{it-1}	1.017	0.951	1.048	0.459	0.474	0.496
(sd)	(0 .002)	(0.006)	(0.004)	(0.000)	(0.000)	(0.001)

II. Average estimate of β. (True value in DGP: $\beta = 0.500$)

	Estimators for AR models			Estimators for HAR models		
	RE	FE	BC-FE	MG	EB-MB	BC-MG
	(1)	(2)	(3)	(4)	(5)	(6)
Panel E: $\sigma_\rho = 0$						
x_{it}	0.344	0.521	0.509	0.529		0.523
(sd)	(0.002)	(0.004)	(0.002)	(0.005)		(0.003)
Panel F: $\sigma_\rho = 0.125$						
x_{it}	0.066	0.245	0.059	0.529		0.520
(sd)	(0.008)	(0.021)	(0.030)	(0.005)		(0.003)
Panel G: $\sigma_\rho = 0.250$						
x_{it}	-0.005	0.097	-0.087	0.524		0.514
(sd)	(0.001)	(0.003)	(0.002)	(0.005)		(0.002)
Panel H: $E(\sigma_{\rho,i}) = 0.150$						
x_{it}	0.010	0.122	-0.074	0.535		0.529
(sd)	(0.003)	(0.006)	(0.005)	(0.006)		(0.004)

Note: Cells contain average and standard deviation of estimates over 100 replications. In each replication, observations are drawn from the following DGP: $y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + x'_{i,t}\beta + \varepsilon_{i,t}$, $i = 1, \ldots, 500$, $t = 1, \ldots, 50$ $\alpha_i \sim N(1, 0.25^2)$, $\rho_i \sim N(0.5, \sigma_\rho^2)$, $\beta = 0.5$, $x_{it} = \bar{x}_i + \nu$, $\bar{x}_i \sim N(0,1)$, $\nu \sim N(0, 0.025^2)$, $\varepsilon_{i,t} \sim N(0, 0.5^2)$, $Corr(\alpha_i, \rho_i) = -0.3$, $Corr(\rho_i, \bar{x}_i) = 0.5$, $Corr(\alpha_i, \bar{x}_i) = -0.8$, $y_{i0} \sim N(0, 0.5^2)$. In the rare instance that a particular draw of ρ_i is realised outside of the interval (-0.99,0.99), it is recoded as either -0.99 or 0.99, whichever is closer.

Table 2: Monte Carlo simulation results: Non-zero correlation

I. Average estimate of $E(\rho_i)$. (True value in DGP: $E(\rho_i) = 0.500$)

| | Estimators for AR models | | | Estimators for HAR models | | |
	RE	FE	BC-FE	MG	EB-MG	BC-MG
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: $\sigma_\rho = 0$						
y_{it-1}	0.615	0.475	0.500	0.455	0.469	0.499
(sd)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Panel B: $\sigma_\rho = 0.125$						
y_{it-1}	0.994	0.889	1.033	0.461	0.477	0.505
(sd)	(0.011)	(0.026)	(0.032)	(0.001)	(0.001)	(0.002)
Panel C: $\sigma_\rho = 0.250$						
y_{it-1}	1.027	0.989	1.028	0.460	0.475	0.498
(sd)	(0.000)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Panel D: $E(\sigma_{\rho,i}) = 0.150$						
y_{it-1}	1.019	0.961	1.042	0.459	0.474	0.498
(sd)	(0.002)	(0.008)	(0.003)	(0.003)	(0.004)	(0.004)

II. Average estimate of β. (True value in DGP: $\beta = 0.500$)

| | Estimators for AR models | | | Estimators for HAR models | | |
	RE	FE	BC-FE	MG	EB-MG	BC-MG
	(1)	(2)	(3)	(4)	(5)	(6)
Panel E: $\sigma_\rho = 0$						
x_{it}	0.295	0.527	0.505	0.536		0.520
(sd)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)
Panel F: $\sigma_\rho = 0.125$						
x_{it}	0.052	0.169	-0.042	0.532		0.517
(sd)	(0.010)	(0.025)	(0.036)	(0.002)		(0.002)
Panel G: $\sigma_\rho = 0.250$						
x_{it}	0.015	0.079	-0.095	0.530		0.511
(sd)	(0.001)	(0.002)	(0.001)	(0.002)		(0.002)
Panel H: $E(\sigma_{\rho,i}) = 0.150$						
x_{it}	0.018	0.102	-0.087	0.531		0.519
(sd)	(0.002)	(0.007)	(0.003)	(0.007)		(0.009)

Note: Cells contain average and standard deviation of estimates over 100 replications. In each replication, observations are drawn from the following DGP: $y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + x'_{i,t}\beta + \varepsilon_{i,t}$,
$i = 1, \ldots, 500$, $t = 1, \ldots, 50$ $\alpha_i \sim N(1, 0.25^2)$, $\rho_i \sim N(0.5, \sigma_\rho^2)$,
$\beta = 0.5$, $x_{it} = \bar{x}_i + \nu$, $\bar{x}_i \sim N(0,1)$, $\nu \sim N(0, 0.025^2)$,
$\varepsilon_{i,t} \sim N(0, 0.5^2)$, $Corr(\alpha_i, \rho_i) = -0.3$, $Corr(\rho_i, \bar{x}_i) = 0.5$,
$Corr(\alpha_i, \bar{x}_i) = -0.8$, $y_{i0} \sim N(0, 0.5^2)$. In the rare instance that a particular draw of ρ_i is realised outside of the interval (-0.99,0.99), it is recoded as either -0.99 or 0.99, whichever is closer.

Table 3: ESTIMATION RESULTS OF DIFFERENT PANEL ESTIMATORS

Dependent variables: Various measures of health and health behaviours

	Estimators for AR models			Estimators for HAR models		
	RE	FE	BC-FE	MG	EB-MG	BC-MG
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Self-assessed bad health [0-1]						
y_{it-1}	0.859	0.345	0.468	0.237	0.237	0.268
	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.007)
Obs Estimation sample	330,636	330,636	330,636	330,636	330,636	316,182
Mean y	0.483	0.483	0.483	0.483	0.483	0.483
Obs Grouped mean				8,200	8,199	5,664
Share significant				0.943		
Panel B: Medical expenditures [0,inf)						
y_{it-1}	0.299	0.182	0.217	0.111	0.131	0.040
	(0.020)	(0.019)	(0.019)	(0.008)	(0.006)	(0.073)
Obs Estimation sample	318,467	318,467	318,467	318,467	318,467	304,883
Mean y	143.541	143.541	143.541	146.230	146.230	149.576
Obs Grouped mean				7,827	7,826	5,634
Share significant				0.743		
Panel C: Doctor visit [0,1]						
y_{it-1}	0.413	0.168	0.223	0.150	0.150	0.154
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)
Obs Estimation sample	316,619	316,619	316,619	316,619	316,619	303,069
Mean y	0.343	0.343	0.343	0.348	0.348	0.348
Obs Grouped mean				7,688	7,687	4,942
Share significant				0.964		
Year fixed effects	✓	✓	✓	✓	✓	✓
Month fixed effects	✓	✓	✓	✓	✓	✓
Quadratic in age	✓	✓	✓	✓	✓	✓
Clustering household-level	✓	✓	✓	✓	✓	✓

Notes: Table shows estimation results of the various linear dynamic panel data models shown in (1) and (2), its coefficients and clustered standard errors on the household level in brackets. Columns display various dynamic estimation approaches, (1) OLS-Random effects, (2) OLS-FE, (3) FE Jacknife - bias correction, (4) and (5) estimate a $\hat{\rho}_i$ for each person and summarise them via: (4) uses a grouped mean approach and (5) and empirical Bayes corrected mean. Panel A - shows results of self assessed bad health 0-1; B- Out-of pocket health expenditure in Singaporean dollar, C - an indicator whether they had to visit a doctor in the last month; and, D - an indicator whether they had any tobacco expenditure last month.
Source: SLP v53, own calculations.

Table 4: CORRELATION MATRIX BETWEEN ESTIMATES OF INDIVIDUAL STATE DEPENDENCE (ρ_i) AND INDIVIDUAL LEVELS (α_i) ACROSS HEALTH OUTCOMES

Variables	α_i^{SAH}	α_i^{Exp}	α_i^{Doc}	ρ_i^{SAH}	ρ_i^{Exp}	ρ_i^{Doc}
α_i^{SAH}	1					
α_i^{Exp}	**0.517** (0.000) [8,603]	1				
α_i^{Doc}	**0.543** (0.000) [8,610]	**0.968** (0.000) [8,603]	1			
ρ_i^{SAH}	**-0.597** (0.000) [8,200]	**0.020** (0.069) [8,195]	**-0.009** (0.436) [8,180]	1		
ρ_i^{Exp}	**0.003** (0.795) [7,827]	**-0.035** (0.002) [7,827]	**-0.017** (0.137) [7,816]	**0.016** (0.166) [7,495]		
ρ_i^{Doc}	**-0.073** (0.000) [7,684]	**-0.016** (0.173) [7,681]	**0.006** (0.603) [7,666]	**0.118** (0.000) [7,367]	**0.089** (0.000) [7,263]	1

Notes: Cells contain: in boldface, pairwise correlation coefficients for α_i and ρ_i ; in parentheses, p-values for the test of correlation being equal to 0; and in brackets, the number of observations used for the test. Outcome abbreviations: SAH – self-assessed bad health, Exp – medical expenditures, Doc – doctor visits.
Source: SLP v53, own calculations.

Table 5: ECONOMIC GRADIENTS IN STATE-DEPENDENCE, FINITE MIXTURE MODEL, CONSTANTS-ONLY SPECIFICATION

Dependent variables: Estimated individual state dependence $\hat{\rho}_i$

	Subjective bad health		Medical expenditures		Doctor visits	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
	(1)	(2)	(3)	(4)	(5)	(6)
N	8,153		7,683		7,671	
AIC	1,964.205		-118.752		-1,518.802	
BIC	1,999.236		-84.019		-710.167	
Class probabilities	0.812	0.188	0.228	0.772	0.165	0.835
Class means	0.155	0.581	-0.026	0.142	-0.056	0.189
Class σ	0.053	0.028	0.002	0.078	0.002	0.060

Notes: Estimates from model (7)-(8). AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. Class probabilities: Estimates of π (class 1) and $1 - \pi$ (class 2).
Source: SLP v53, own calculations.

Table 6: ECONOMIC GRADIENTS IN STATE-DEPENDENCE, FINITE MIXTURE MODEL, SOCIO-ECONOMIC VARIABLES SPECIFICATION

Dependent variables: Estimated individual state dependence $\hat{\rho}_i$

	Subjective bad health		Medical expenditures		Doctor visits	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
	(1)	(2)	(3)	(4)	(5)	(6)
Female (Yes/No)	-0.002	-0.008	-0.001	-0.000	0.000	0.008
	(0.005)	(0.007)	(0.004)	(0.008)	(0.004)	(0.007)
Married (Yes/No)	-0.002	-0.008	-0.001	-0.008	-0.006	0.010
	(0.006)	(0.009)	(0.006)	(0.010)	(0.007)	(0.009)
Age in years/10	-0.066	0.104	-0.080	0.418	0.063	0.150
	(0.106)	(0.150)	(0.086)	(0.167)	(0.100)	(0.146)
Age squared	0.005	-0.009	0.008	-0.034	-0.005	-0.014
	(0.009)	(0.013)	(0.007)	(0.014)	(0.008)	(0.012)
Years of schooling/10	-0.005	0.020	0.014	0.029	0.003	-0.018
	(0.007)	(0.009)	(0.005)	(0.010)	(0.005)	(0.009)
log HH income	-0.006	0.002	0.003	0.013	0.002	0.001
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
N	7,818		7,379		7,357	
AIC	1,498.263		-152.162		-700.083	
BIC	1,616.655		-34.753		-582.725	
Class probabilities	0.111	0.889	0.228	0.772	0.165	0.835
Class means	-0.028	0.268	-0.027	0.142	-0.055	0.189
Class σ	0.002	0.074	0.002	0.077	0.002	0.060

Notes: Estimates from model (7)-(8). Standard errors robust to heteroskedasticity and clustering at the household level. AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. Class probabilities: Estimates of π (class 1) and $1 - \pi$ (class 2).
Source: SLP v53, own calculations.

Table 7: ECONOMIC GRADIENTS IN STATE-DEPENDENCE, FINITE MIXTURE MODEL, FULL SPECIFICATION

Dependent variables: Estimated individual state dependence $\hat{\rho}_i$						
	Subjective bad health		Medical expenditures		Doctor visits	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
	(1)	(2)	(3)	(4)	(5)	(6)
Female (Yes/No)	-0.002	-0.014	-0.002	0.003	-0.004	0.009
	(0.007)	(0.008)	(0.005)	(0.009)	(0.005)	(0.008)
Married (Yes/No)	-0.000	-0.013	-0.003	-0.016	-0.008	-0.001
	(0.007)	(0.010)	(0.006)	(0.011)	(0.008)	(0.010)
Age in years/10	0.061	0.192	-0.013	0.315	0.072	0.050
	(0.120)	(0.163)	(0.093)	(0.185)	(0.109)	(0.153)
Age squared	-0.006	-0.016	0.002	-0.025	-0.006	-0.005
	(0.010)	(0.014)	(0.008)	(0.016)	(0.009)	(0.013)
Years of schooling/10	-0.003	0.015	0.012	0.021	0.001	-0.003
	(0.009)	(0.010)	(0.006)	(0.012)	(0.005)	(0.010)
log HH income	-0.003	0.002	0.001	0.016	0.001	0.004
	(0.003)	(0.004)	(0.002)	(0.005)	(0.002)	(0.004)
Risk attitudes (1-10)	0.008	0.008	0.001	-0.001	-0.002	0.012
	(0.015)	(0.016)	(0.009)	(0.018)	(0.009)	(0.015)
Extraversion (std)	0.011	0.005	-0.004	-0.011	-0.007	0.022
	(0.006)	(0.008)	(0.004)	(0.009)	(0.005)	(0.007)
Agreeableness (std)	0.010	0.006	0.003	0.020	-0.002	-0.016
	(0.008)	(0.008)	(0.004)	(0.009)	(0.006)	(0.008)
Conscientiousness (std)	-0.008	0.018	0.008	0.003	0.003	-0.017
	(0.008)	(0.008)	(0.004)	(0.009)	(0.007)	(0.008)
Neuroticism (std)	0.007	0.030	0.003	0.023	-0.002	0.004
	(0.007)	(0.007)	(0.004)	(0.008)	(0.005)	(0.007)
Openness (std)	-0.010	-0.011	-0.002	0.004	0.005	-0.004
	(0.008)	(0.008)	(0.005)	(0.009)	(0.005)	(0.008)
N	5,746		5,500		5,497	
AIC	225.600		-929.509		-1,518.802	
BIC	418.632		-737.746		-1,327.055	
Class probabilities	0.129	0.871	0.251	0.749	0.175	0.825
Class means	-0.027	0.298	-0.024	0.161	-0.054	0.197
Class σ	0.002	0.061	0.002	0.067	0.002	0.048

Notes: Estimates from model (7)-(8). Standard errors robust to heteroskedasticity and clustering at the household level. AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. Class probabilities: Estimates of π (class 1) and $1 - \pi$ (class 2).
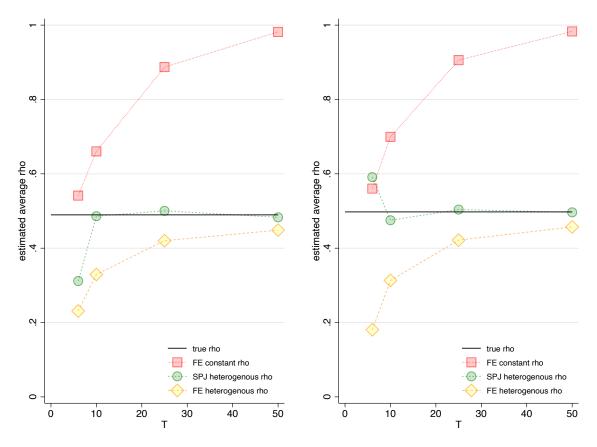
Source: SLP v53, own calculations.

Figure 1: Monte Carlo simulations: Estimated average ρ_i over samples with different numbers of periods (T)

Note: The figure plots average estimates of $E(\rho_i) = 0.5$ over 100 replications for FE ("FE constant rho"), MG estimator ("FE heterogeneous rho") and BC-MG ("SPJ heterogenous rho") for the DGP described in the notes of Table 1 and where $\sigma_\rho = 0.25$. In the right-hand-side panel, 20 percent of observations have been deleted at random in each replication.
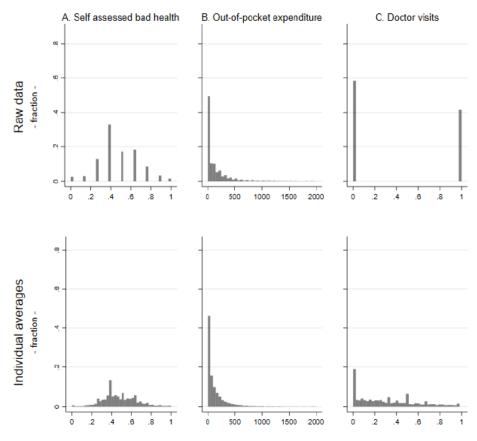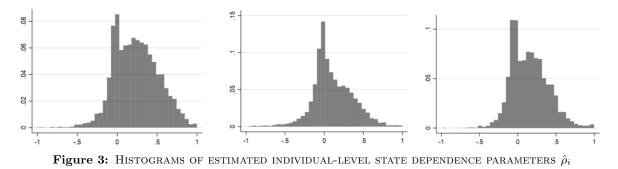
Figure 2: Histograms of outcome variables and their panel means

Note: Histograms of the outcome variables [top] and of their individual averages over time $(\bar{y}_i = \sum_{t=1}^{T_i} y_{it}/T_i)$ [bottom].

Source: SLP v53, own calculations.

Figure 3: HISTOGRAMS OF ESTIMATED INDIVIDUAL-LEVEL STATE DEPENDENCE PARAMETERS $\hat{\rho}_i$

Note: Histograms of the estimated individual slopes ρ_i on the lagged dependent variable of model (2) corresponding to the estimates of Column (4) in Table 3 for each of the three outcomes self-assessed bad health (left figure), medical expenditures (middle) and doctor visits (right).
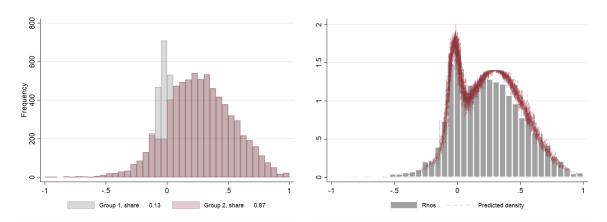
Source: SLP v53, own calculations.

Figure 4: MODEL FIT — FINITE MIXTURE MODEL FOR PERSISTENCE IN SELF-ASSESSED BAD HEALTH, FULL SPECIFICATION

Note: Left-hand side: Histograms of predicted classes. Right-hand side: Point-wise predicted marginal density against histogram of $\hat{\rho}_i$. Graphs are based on estimates from Table 7.

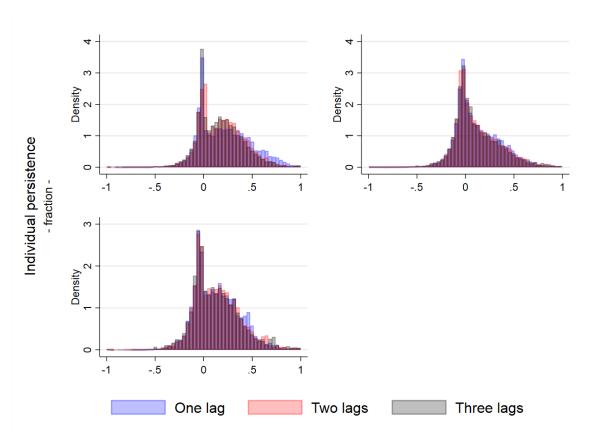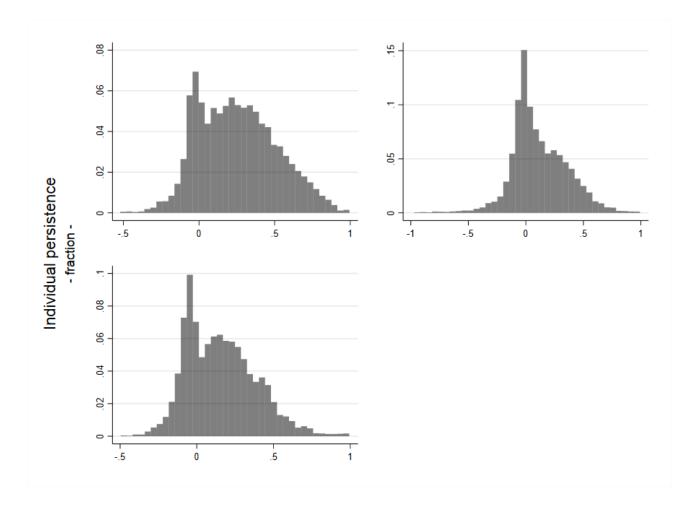*Source:* SLP v53, own calculations.

Appendix

Figure A1: Histograms of estimated individual-level state dependence parameters $\hat{\rho}_i$, various lags

Note: Histograms of individual-specific coefficients on first lag of dependent variable from HAR models. Blue for baseline HAR(1) model (2), identical to Figure 3; red for a HAR(2) model with first and second lag of the dependent variable ($y_{it-1}.y_{it-2}$); grey for a HAR(3) model with first, second and third lag of the dependent variable ($y_{it-1}.y_{it-2}, y_{it-3}$). Outcomes: Persistence in self-assessed bad health (top left), medical expenditures (top right), doctor visits (bottom).

Source: SLP v53, own calculations.

Figure A2: Histograms of estimated individual-level state dependence parameters $\hat{\rho}_i$, for T>30

Note: Histograms analogous to Figure 3 but based only on $\hat{\rho}_i$ of individuals observed at least 30 times. Outcomes: Persistence in self-assessed bad health (top left), medical expenditures (top right), doctor visits (bottom).

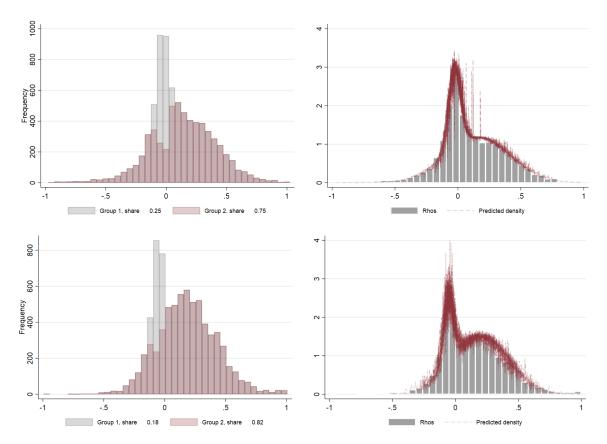*Source*: SLP v53, own calculations.

Figure A3: MODEL FIT — FINITE MIXTURE MODEL FOR PERSISTENCE IN MEDICAL EXPENDITURES AND DOCTOR VISITS, FULL SPECIFICATION

Note: Left-hand side: Histograms of predicted classes. Right-hand side: Point-wise predicted marginal density against histogram of $\hat{\rho}_i$. Top: Medical expenditures. Bottom: Doctor visits. All graphs based on estimates from Table 7.

Source: SLP v53, own calculations.